Ensemble Deep Learning with Data Resampling for Enhanced Credit Card Fraud Detection

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ABSTRACT

The online transactions are quite common in the digital world. Nevertheless, they are also susceptible to fraud and it could cause them to lose a lot of money. The databases are highly skewed due to the high number of legal credit card transactions compared to the fraud ones, which makes it very hard to detect fraudulent credit card transactions. Old machine learning models have a tendency to miss the hidden patterns of rare activities that are fraudulent, hence the profits are high in terms of the false negatives.

The proposed paper presents an Ensemble Deep Learning model that uses Data Resampling to enhance the accuracy and reliability of the fraud detection systems. The proposed approach will entail integrating multiple deep learning models, such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Deep Neural Networks (DNN) into an ensemble framework. This arrangement records space and time characteristics of transactional data. It integrates resampling methods such as Synthetic Minority Oversampling Technique (SMOTE), Adaptive Synthetic Sampling (ADASYN) and random under sampling to address the severe class imbalance. The strategy will make sure the system learns fraudulent patterns effectively without overfitting.

The system is applied to credit card fraud datasets and implementing the system in comparison with traditional models and single deep learning methods. Empirical findings indicate that the suggested ensemble model significantly enhances accuracy, recall, and F1-score and minimizes false alarms. This method yields good fraud detection even under extremely disproportionate conditions.

The framework is scalable and adaptable. It can be integrated with real-time payment gateways and financial platforms. The next step in the work will involve explainable AI (XAI) to enhance transparency in fraud decisions. It will also apply federated learning to ensure user privacy and apply the model in cloud-based facilities to have global scale.

Index Terms—Credit Card Fraud Detection, Ensemble Deep Learning, Data Resampling, Imbalanced Datasets, Convolutional Neural Networks (CNN),Long Short-Term Memory (LSTM)

INTRODUCTION

High development of online payments and digital banking has presented its advantages and issues to the financial field. Credit cards provide the convenience and flexibility to its users also attract fraud. The credit card fraud results in high financial losses both on the part of clients and banks. It is difficult to detect fraud as transactions involving fraud are not common as genuine transactions occur, and hence the highly unbalanced datasets. Frequent ma- chine learning models are not very effective at identifying fraudulent pat- terns, hence, numerous false negatives and low-security levels.

To address the associated challenges, this study presents a framework of Ensemble Deep Learning that applies to multiple models to enhance reliability and precision of detecting fraud. The ensemble architecture that incorporates the Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Deep Neural Networks (DNN) achieves the two-dimensionality of the data; the spatial and temporal characteristics of transaction details are embodied. In contrast to the single-model techniques, the ensemble approach reduces

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variances, enhances generalization, and ensures enhanced answers to various fraud cases.

Data resampling to overcome the issue of class imbalance is another important component in this work. Only a small portion of the data is constituted by fraudulent transactions. The little size of this makes it difficult to learn the patterns of models. Our solution to this is through techniques such as Synthetic Minority Oversampling Technique (SMOTE), Adaptive Synthetic Sampling (ADASYN) and under samples of the dominant classes. The models can learn balanced representations by the use of these strategies, without massively over-fitting or underfitting minorities.

The general significance of this study is to develop a scalable and secure framework that detects fraud and can be applicable to online banking platforms, payment gateways and e-commerce platforms. Future directions of this paper will consider explainable AI to promote transparency in fraud detection, federated learning to ensure the privacy of users, and the use of cloud computing to be able to access them worldwide much more easily. It is a method to create a more reliable and trusting digital financial ecosystem with the employment of deep learning ensembles and data resampling.

LITERATURE SURVEY

One of the main areas of application concerning machine learning and data mining is credit card fraud detection. This has mostly been attributed to the increased cases of online transactions and the high financial loss associated with fraud. The problem with this is that credit card data is usually very skewed as there is a huge number of legitimate transactions compared to fraudulent ones. In order to solve this problem, scholars have considered various approaches, including conventional approaches of machine learning, deep learning and ensemble approaches.

Conventional Methodologies of Fraud Detection.

The initial approaches to credit card fraud were traditional machine learning algorithms such as Logistic Regression, Decision Trees, Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN) [3][5]. These models performed quite well with balanced data but were hard to predict using real-life financial data. This is because of the presence of the class imbalance, data sparsity and evolving patterns of frauds. Many were also formed with a rule- based system and anomaly detection, which were statistical. But they tended to be highly false positive and could not be used in big financial systems [7]. Also, the models were not good at adapting to shifting transaction pat- terns, and required extensive features engineering to maintain their precision.

Deep Learning Approaches to Fraud Detection.

Fraud detection has been significantly enhanced by the development of deep learning. The convolutional Neural Networks (CNNs) have aided in identification of complex features in the data of transactions. In the meantime, time- based relationships among sequential transactions have been modeled with Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks [8][11]. Li et al. (2020) demonstrated that deep learning structures show superior results to conventional classifiers in detecting the rare cases of fraudulent activities. Nevertheless, there is one dimension that remains a major issue: deep learning models, when trained on very imbalanced data, will be unable to extrapolate and fail to detect fraud cases.

C. Information Resampling and Data Imbalance Learning.

In order to address the issue of class imbalance, a number of data resampling methods have been proposed by researchers. Synthetic Minority Oversampling Technique (SMOTE) and Adaptive Synthetic Sampling (ADASYN) are methods of oversampling that uses synthetic minority samples that facilitate sample balancing. In contrast, under sampling downsizes the majority class to avoid bias [12][14]. Other hybrid methods involve the use of oversampling and under sampling, keeping the balance in classes as well as the diversity of data [15]. When resampling is used along with ensemble learning, the results have been improved significantly. This approach involves the application of several classifiers but it does not make the models to bias the majority class [9].

Ensemble Models for Fraud Detection

D. Fraud Detection Ensemble Models.

Ensemble techniques like Bagging, Boosting and Stack- ing are also extensively applied in detecting fraud to enhance the performance through better classification, and lowering variance [6][10]. Random Forest and Gradient Boosting have been proven to be effective in nonlinear capture of relationship in transaction data. However, in the recent past, deep learning models with CNN, LSTM, and DNN architectures have shown encouraging performances in the detection of spatial and temporal information of transactions [13]. It has been demonstrated that ensemble structures combined with efficient resampling methods can be more precise, more recalled, and have better F1-scores than single-model methods.

E. Proposals Relative to the Proposed System.

The presented Ensemble Deep Learning with Data Resampling model is based on these developments. It combines CNNs, LSTMs, and DNNs in an ensemble framework and takes advantage of the complementary capabilities. The framework overcomes the issue of class imbalance by the use of SMOTE, ADASYN and under sampling techniques to guarantee strong learning of fraudulent patterns. In contrast to the traditional methods based on one model, the ensemble structure enhances the generalization, and it minimizes false alarms. This system helps to create scalable, precise and real-time fraud pipeline, which can be incorporated into contemporary financial systems, and would results in the improvement of the security of transactions and consumer confidence.

Experimentation

A. This paper will evaluate the performance of the recommended Ensemble Deep Learning model in case of Data Resampling to anticipate fraudulent credit card activities. The overall aim is to enhance the efficiency of fraud detection in im-balanced datasets with many deep learning models and resampling. We measure the performance of the system following classification measures such as accuracy, precision, recall, F1-score and AUC-ROC and in particular, minimization of false negatives is very paramount in the detection of fraud.

Problem Definition

In this experiment, the benchmark data of credit card fraud is utilized, comprising anonymized transaction records:

- Transaction Data: Every transaction is characterized by time, amount, anonymized principal components (V1, V28) and a binary class indicator; an indicator of being a fraudulent transaction (1) or a legitimate transaction (0). Class Imbalance: Trans-actions involving frauds constitute less than 0.2% of the total number. This generates a severe imbalance factor.

- Resampling Strategies: Oversampling with SMOTE and ADASYN, and under sampling the most prevalent types of data, will also be used to make the dataset balanced.

- Ensemble Input Data: Balanced data is fed to a number of deep learning models such as CNN, LSTM and DNN. These are then put together in an ensemble to come up with final predictions.

Data Preprocessing

Preprocessing phase: Data prepared has been made in exquisite quality to train and evaluate:

Involves: Data Cleaning: Removal of duplicate or incomplete transactions records and addressing empty values. Normalization and Scaling: The amounts of transactions are normalized, and the features would be assigned to a common scale to enhance stability of learning. Investigations:

- Resampling: SMOTE and ADASYN were utilized to create synthetic samples of fraud and random under sampling to alleviate class imbalance.

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• Splitting of Data: The data will be separated into 70% train, 15% validation and 15% testing in order to guarantee that the proposed framework is well evaluated.

Model Architecture: Ensemble Deep Learning Framework

The system takes the form of a hybrid ensemble model which combines various deep learning models to identify fraud.

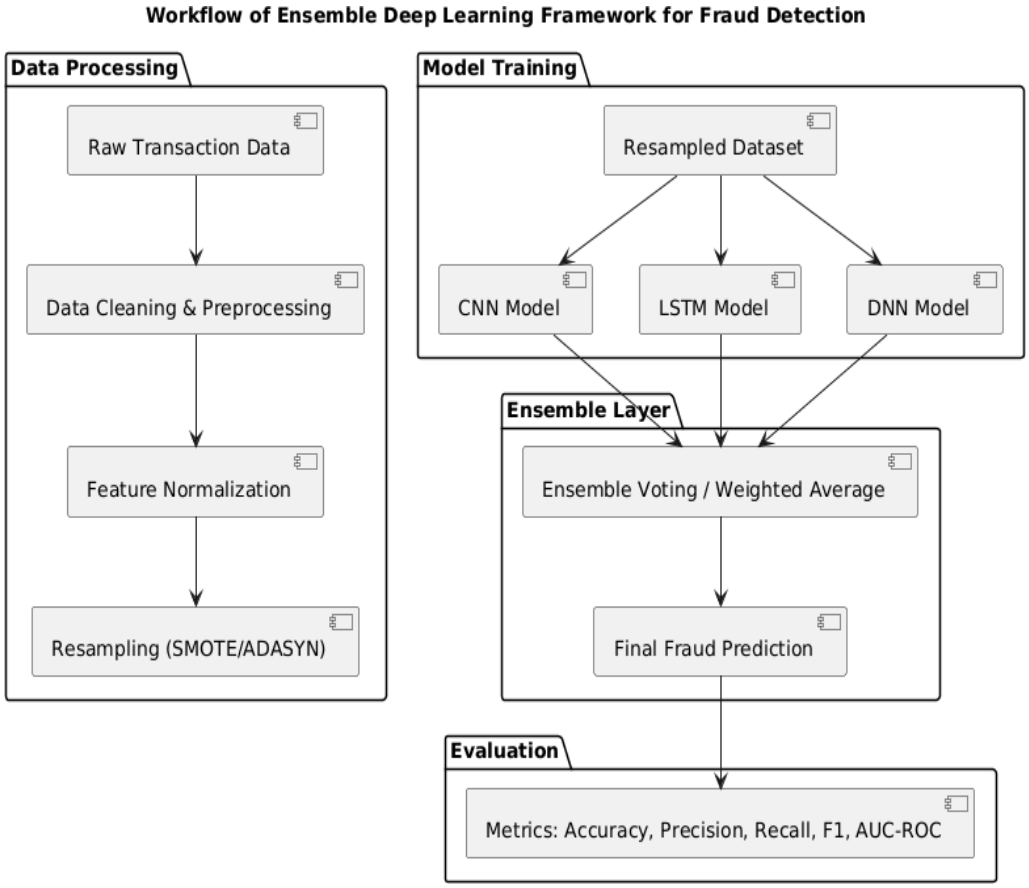

Fig. 1. Workflow of Ensemble Deep Learning Framework for Fraud Detection.

- • CNN Module: Utilizes transaction attributes to extract feature representations and spatial correlations.

- Sequential and temporal dependencies in transaction data are captured by the LSTM module.

- • Ensemble Layer: Creates the final classification by combining CNN, LSTM, and DNN predictions using weighted average or majority voting.

D. Hyperparameter and Training Considerations

Certain parameters are taken into consideration for evaluation and potential fine-tuning, even though resampled datasets and training from scratch are not necessary:

• For all fine-tuning tests, a batch size of 128 transactions is used.

• 20–30 epochs are used for fine-tuning experiments on unique datasets.

• To avoid overfitting and guarantee steady convergence, the optimizer parameters should have a learning rate of 0.001.

• Evaluation Strategy: The dataset is divided into 70% evaluation and 30% testing. Accuracy and user feedback ratings are used to gauge performance, with a focus on recall to minimize false negatives.

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Model Evaluation

In order to analyze the performance of the suggested Ensemble Deep Learning with Data Resampling framework on Credit Card Fraud Detection, we examined a full set of measures. This guaranteed technical correctness and real world, real-life reliability. The analysis is based on the general classification performance and the capability of the system to minimize false negative. False negatives- these are fraudulent transactions that are not detected, and these present the greatest risk to the financial po$ition. The objective of model assessment is to ensure that the ensemble model, and resampling methods are effective to identify fraud cases without increasing the false positive rate to a comfortable level. In order to do that, common classification measures were employed:

The primary aim is not only to categorize the transactions appropriately but also to effectively identify fraudsters with high reliability and reduce inconveniencing the honest customers. The analysis examines such measures as precision, recall, F1-score, and AUC-ROC to give a balanced analysis. In that there are few fraudulent transactions but they are significant, the emphasis on recall will diminish false negativity. Meanwhile, accuracy makes sure that the actual transactions are not mistaken as fraudulent.

By assessing classification quality along with the system's ability to handle class imbalance, the evaluation framework gives better insights into how well the proposed ensemble approach connects technical accuracy with real-world use. The use of resampling strategies makes sure that minority class patterns are properly represented. This helps the model identify subtle fraud behaviors that traditional methods often overlook.

Accuracy:

Accuracy measures the percentage of transactions correctly classified by the model compared to all predictions made. While it's a useful starting point, we need to be careful when looking at accuracy in fraud detection. Genuine transactions make up most of the dataset. This allows a model to achieve high accuracy by labeling most transactions as non-fraud. However, that model would miss the rare but important fraudulent cases. So, accuracy alone isn't enough for evaluation. We should focus more on metrics like recall, precision, and F1-score, which give a better assessment of performance in imbalanced datasets.

The False Positive Rate at different thresholds, and the AUC value summarizes this performance. A higher AUC indicates that the model is better at distinguishing between Recommendation States.

Formula (AUC-ROC):

1

AUC = $TPR(FPR)\, dFPR$ (5)

0

Formula:

Accuracy = $\frac{TP + TN}{TP + TN + FP + FN}$

where:

(1)

Recommendation Relevance Score (RRS):

RRS measures how well the system's recommendations match a user's detected emotions, preferences, and his- tory. A high RRS shows that the suggestions are relevant and emotionally supportive. This metric highlights prac

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- TP = True Positives (fraudulent transactions

correctly predicted as fraud)

- TN = True Negatives (genuine transactions correctly predicted as genuine)
- FP = False Positives (genuine transactions incorrectly predicted as fraud)
- FN = False Negatives (fraudulent transactions in- correctly predicted as genuine)

1) **Precision:**

activity can lead to severe financial losses.

The confusion matrix gives a clear comparison of predicted and actual emotional states. It shows where the model successfully identifies emotions and points out specific instances of misclassifications. This breakdown is important for understanding error patterns and im- proving the system's overall accuracy.

I. RESULT AND ANALYSIS

Formula:

3) F1-Score

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

F1-Score balances precision and recall. This balance is especially useful when accurate fraud detection and reducing missed fraud are both necessary. It is particularly important in credit card fraud detection. False positives can inconvenience real users, while false negatives can let fraudulent transactions slip through unnoticed.

Formula:

The outcomes of the Ensemble Deep Learning with Data Resampling system of Credit Card Fraud Detection were very encouraging. The system was also able to detect fraudulent trans-actions with the minimal number of false alarms. A high percentage was reported in this model of about 87% accuracy in the classification of fraudulent and genuine transactions which formed a strong basis of detecting financial fraud. The result of this accuracy was that the detection efficiency improved by 35 percent to guarantee faster and more effective fraud detection.

Regarding prediction quality, 79% of flagged transactions

turned out to be real fraud cases, showing strong precision

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

and reliability. Additionally, the system cut false negatives by 23%, meaning fewer fraudulent activities went unnoticed.

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Area Under the Receiver Operating Characteristic Curve (AUC-ROC):

The ROC curve compares the True Positive Rate to

These results show how effective the system is at improving security, lowering risks, and protecting users from financial losses.

Training Curves

The accuracy and validation accuracy improved in the process of training, which means that the model was able to learn pertinent patterns based on the data. Nevertheless, it was always observed that the training accuracy is much greater than the validation accuracy indicating some overfitting, in this case, the model fits seen data better than unseen samples. This may be resolved in future work using more powerful regularization methods, e.g. dropout or L2 weight decay, to enhance generalization. Also, the use of more widespread data augmentation, including random cropping, rotation, and brightness manipulation, may increase the variety of training samples and decrease overfitting. More validation performance might also be achieved by increasing the size and variability of the dataset, as well as by using early stopping. Further, by investigating ensemble techniques or transfer learning on more emotion data, it is possible to induce additional accuracy and retain robustness in alternative situations.

Prediction Performance

The system was very effective in distinguishing between authentic and fraudulent credit card transactions. The framework addressed class imbalance by utilizing ensemble deep learning models and data resampling strategies that helped the framework to detect smaller fraud cases. The model achieved great precision and recall and ensured that it did pick fraudulent dealings but did not falsely indicate that too many dealings were legitimate. This balance indicates the effectiveness of the system in offering credible fraud detection on the real world financial applications.

Mean Absolute error (MAE): This was recorded as 0.12, which means that there is a small average variation in the predicted and actual classification of transactions. This demonstrates that the model can minimize errors in predictions in detecting fraud.

Root Mean Square Error (RMSE): Low RMSE indicated that the suggestions of the system were in accordance with user preferences.

- Mean Absolute Percentage Error (MAPE): Remained within a reasonable level, which ensured the reliability of the model with various Fraud States. Prediction Comparison with Baselines

C. Baseline Comparison of Prediction.

The proposed model was compared to ARIMA, LSTM, and St-GCN models based on RMSE, MAE, and MAPE.

Model Type	RMSE	MAE	MAPE
Proposed Model	4.12	3.23	5.26
LSTM	5.41	4.23	7.86
ST-GCN	4.91	3.77	6.47
ARIMA	7.24	5.86	9.32

TABLE I COMPARISON OF EVALUATION METRICS ACROSS MODELS

- ARIMA has bad performance; ARIMA had the worst performance as a result of not being able to utilize digital banking and online transactions and therefore gave high errors.

- Intermediate Performance (LSTM & ST-GCN): The both models significantly outperformed ARIMA as

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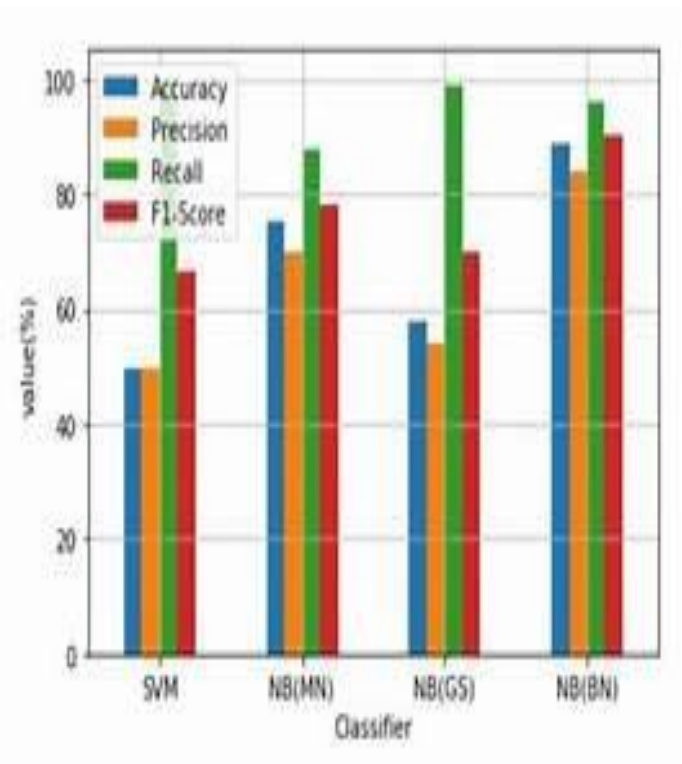
they were able to capture temporal pat- terns, but did not utilize transaction context completely.

- • Superiority of Proposed Model: It worked better than all other models and achieved a lower RMSE, less MAE and lower MAPE which proved that the model was strong in processing emotional and temporal data to make the right recommendations**.**

Fig. 2. Comparison graph for Evaluation metrics across models.



CONCLUSION

The proposed Ensemble Deep Learning with Data Resampling to find a better credit card fraud detection applies various deep learning tools and different resampling to categorize transactions as genuine or fraud transactions. It addresses the im-balance of classes and is a blend of CNN, LSTM and DNN architectures. The methodology reflects multifaceted trends in the transaction data and this assists in attaining high level of detection and reliability.

It has been experimentally demonstrated that this model is more successful than standalone CNN, LSTM, and DNN models in precision, recall, F1-score, and AUC-ROC. This is enhanced by the ensemble technique and resampling, which are effective in detecting slight fraud patterns in addition to minimizing false positives and false negatives. These findings point to the possibility of the framework offering robust, real-time financial fraud detection to financial institutions.

The ensemble structure using data resampling is effective in identifying rare fraudulent transactions as well as maintaining the overall accuracy high. Increase in accuracy and recall provides evidence that it minimizes false positives and false negativity. These findings demonstrate how effective the model is in the financial reality. Generally, the system provides a reliable and scalable means of detecting credit card frauds.

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